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Towards Using a Physio-cognitive Model in Tutoring for Psychomotor Tasks

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Abstract. We report our exploratory research of psychomotor task training in intelligent tutoring systems (ITSs) that are generally limited to tutoring in the desktop learning environment where the learner acquires cognitively oriented knowledge and skills. It is necessary to support computer-guided training in a psychomotor task domain that is beyond the desktop environment. In this study, we seek to extend the current capability of GIFT (Generalized Intelligent Framework for Tutoring) to address these psychomotor task training needs. Our approach is to utilize heterogeneous sensor data to identify physical motions through acceleration data from a smartphone and to monitor respiratory activity through a BioHarness, while interacting with GIFT simultaneously. We also utilize a computational model to better understand the learner and domain. We focus on a precision-required psychomotor task (i.e., golf putting) and create a series of courses in GIFT that instruct how to do putting with tactical breathing. We report our implementation of a physio-cognitive model that can account for the process of psychomotor skill development, the GIFT extension, and a pilot study that uses the extension. The physio-cognitive model is based on the ACT-R/Φ architecture to model and predict the process of learning, and how it can be used for improving the fundamental understanding of the domain and learner model. Our study contributes to the use of cognitive modeling with physiological constraints to support adaptive training of psychomotor tasks in ITSs.

Keywords: Psychomotor tasks, skill learning, learner modeling, GIFT, ACT-R/Φ, Tactical breathing

1 Introduction

In the past, computer-based systems for training have shown to impact learning in several tasks, including procedural troubleshooting tasks [e.g., 1], mathematics and physics problem-solving tasks [e.g., 2, 3, 4], and others [e.g., 5]. These tasks are not highly related to psychomotor tasks. Psychomotor skill development would benefit from a type of training that is beyond the desktop environment. [6, 7].

1.1 Significance of the Work

The goal of training is to transfer the initial knowledge and skill set to a procedural form in a later stage, which is called *proceduralization* in ACT-R [Adaptive Control of Thought-Rational, 8] and *chunking* in other theories [9]. Moving the skill set to a later stage in an optimal way is a challenge, which entails high inter-dependence with training effectiveness.

When it comes to training, we can consider assessment of learning and performance [10] in the theory of learning stages [e.g., 11]. But, the computational understanding is limited, and it is necessary to simultaneously consider cognitive states (e.g., attention), physical activities (e.g., walking, hitting, climbing, etc.), and physiological states (e.g., heart rate and respiratory rate), while the learner is achieving the goal of training. The current ITSs mostly do not address this issue—e.g., ITSs do not account for physiological responses that are affected by the cognitive learning process. The training of skill and resulting mastery can be improved with finer grain learner and domain models based on an understanding of cognitive, physical and physiological factors.

To address this issue, it is necessary to extend the learner and domain modeling capacity. For example, the learner would need to acquire a physiological control skill (i.e., slow breathing) to improve accuracy in a golf putting task. Thus, we seek to improve the learner and domain modeling capacity based on the ACT-R/Φ architecture. We also seek to incorporate sensors in GIFT for improved assessment in a psychomotor task that is completed beyond the desktop.

1.2 Outlines of the Study

In this paper, we report our implementation of a *physio-cognitive model* of golf putting in ACT-R/Φ [12, 13], and that is based on the previous cognitive task analysis [12-14]. Next, we introduce a study environment where the learner takes a GIFT (Generalized Intelligent Framework for Tutoring) course of tactical breathing and practices a series of putting trials. We test sensors and their incorporation into GIFT to better assess the learner's psychomotor performance while the learner interacts with GIFT. We run a pilot study, measuring a participant's physiological states and physical motions. The offline analysis of the data tells us what further learning analytics is needed to improve the capability. We conclude the paper with a discussion of the lessons learned from our exploration and the suggestions for further development toward the mobile GIFT.

2 Learning and Assessment

2.1 Learning in the Psychomotor Task Domain

A golf putting task consists of subtask skills of: (a) cognitive skills including "judge the line of the ball", "check with hand and grip postures", (b) a physiological control skill including "slow breathing", and (c) physical actions including "walking to the ball" and "hitting the ball". These elements are interdependently connected to produce a precision-required performance [14].

Interestingly, it has been reported that there is a functional relationship between attentional control and psychomotor performance [e.g., 15, 16]. Particularly, skill levels (from a novice to an expert) are related to attentional resources (i.e., step-by-step execution of skill components vs. proceduralized performance). In addition, it has been reported that a physiological change (e.g., respiratory and heart rate) is related to psychomotor performance [17]. Therefore, it can be argued that physiological and cognitive factors are functionally interrelated with psychomotor performance, and an advanced understanding of such factors is highly necessary to improve the precision-required performance in a psychomotor task.

It also has been reported that heart rates are related to degradation of psychomotor performance—i.e., around 115 beats per minute (bpm), fine motor skills begin to deteriorate, and complex psychomotor skills are degraded around 145 bpm, and gross motor skills (e.g., running) start to break down above 175 bpm [17, pp. 31]. As a training strategy, a tactical breathing skill (e.g., slow breathing) is used to address such performance degradation under pressure [e.g., 17]. Furthermore, it is reported that tactical breathing and mental imagery training might mitigate negative effects of stress for police officers [18], and stress management training with tactical breathing is effective in reducing stress in soldiers [e.g., 19]. Thus, it is worth exploring a skill acquisition approach that can reduce and delink memory from a physiological arousal through the physiological control of tactical breathing.

2.2 Assessment with Sensors in the Psychomotor Task Domain

Based on the previous marksmanship study [20], we extend GIFT to use an accelerometer in a smartphone, which supports monitoring motions during the physical practice session in GIFT. We exploit the heterogeneous sensor data from an accelerometer in a smartphone and from a BioHarness to measure respiratory rates simultaneously.

Assessing and instructing the learner beyond the desktop environment would require tools be portable and mobile. These days, there is a stream of research about mobile health with pervasive technology, seeking to enable IoTs (Internet of Things) with embedded microprocessors to identify health related human factors [e.g., 21, 22]. A smartphone features various sensors including an accelerometer, a magnetometer, a gyroscope, and a barometer, and can be useful to better assess the learner state while they are interacting with an ITS beyond the desktop environment. These sensors can be used to discern user activity to determine the learner's skill level [e.g., 23, 24] and to provide contextual change, for example location, which may also be used to alter content [e.g., 25].

The current study focuses on connecting GIFT with an Android smartphone. We utilize acceleration data that is considered as the time rate of velocity change in terms of magnitude or direction. These acceleration data can provide motion analysis of golf swing [e.g., 26], and have been actively used to monitor animal behavior [e.g., 27].

3 The Model

In this section, we introduce our *physio-cognitive* model. Also, it is explained how the model can be used to extend the domain and learner modeling capability in ITSs.

3.1 Extending the Domain and Learner Modeling in ITSs

The domain model is referred to as a repository of knowledge and skills that are being taught. It indicates the scope of the subject matter to be taught to the learner, the sequences of the topics for instruction, and a sequence of interdependent learning objectives [28]. The learner model, as a subset of the domain model, specifies how the learner acquires knowledge and skills in the domain model. It should be able to account for how knowledge and skills are learned through practice.

Domain and learner models—some are grounded on constraint-based models [e.g., 29, 30] or others are grounded on production rule-based models [e.g., 31]—have provided useful information to understand the domain and the relevant task knowledge and skills required in that domain. Domain and learner models consist of knowledge components which is defined as an acquired unit of cognitive function or structure inferred from performance on a set of related tasks [32]. A benefit of such models is that their runnable simulations, providing predictions that can be compared with human data. However, as noted earlier, the domains that have been considered are mostly limited to the cognitive task domain.

The different domains (e.g., a cognitive, psychomotor, and social domain) would affect the way of modeling the domain and learner. In the cognitive domain, one of the objectives of the learner would acquire the maximum number of declarative memory items that are usually specified in the domain model. In the psychomotor domain, the amount of declarative memory items would not be necessarily large, but the learner model would need a finer tuned domain model with a computational understanding of physiological responses interacting with memory and motor modules.

For example, the novice learner would acquire knowledge and skills about the putting task, which can be modeled using a rule-based system (e.g., ACT-R); a similar rule-based system can be also used (e.g., Soar). The learner would go through cognitive processes (e.g., judge the line of the ball) before making an action (hit the ball). At the same time, the learner would control his/her breath to increase accuracy. In seconds, the task may be completed. Compared to other cognitive tasks (e.g., solving an algebra question), the putting task does not necessarily require a lot of symbolic and explicit knowledge components, but it requires a finer granularity of instructions about how to successfully coordinate cognitive, physiological, and physical processes.

3.2 The Physio-cognitive Model

We have developed a computational model for a psychomotor task. The first model [14] produced a simple task time to complete a putting stroke by skill levels, which is based on ACT-R [8]. Fig. 1 gives a high-level view of the version of the model where roughly 50% of productions use declarative memory (ACT-R retrieval requests) as a part of their processing after 5,000 runs (known as 50% expertise, see [33] for a background on the Herbal/ACT-R compilation mechanism used to develop the initial model); the bottom of Fig. 1 also gives the resulting model (with compiled productions).

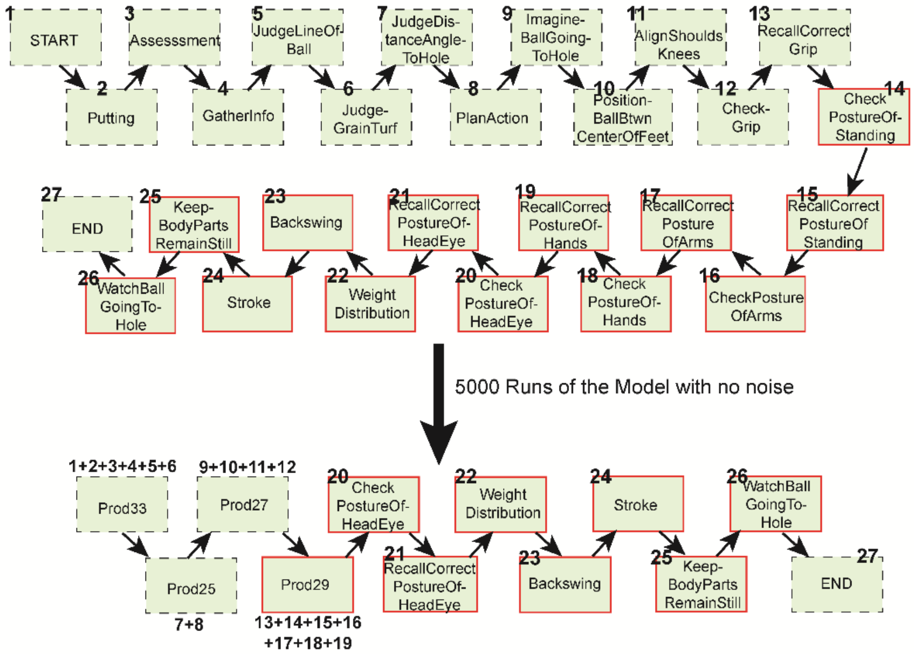

Fig 1. The 50% putting model after 27 rule firing in any given "putt" to 5000 runs with no procedural or declarative memory noise to affect the production firing. The red solid-line boxes represent rules that include a declarative memory component, while the black dotted-line represents rules that do not use declarative memory.

The physio-cognitive model is based on ACT-R/Φ [12, 13]. We chose to use ACT-R/Φ as an architecture to build a learner model because it is a hybrid cognitive architecture with a physiological representation. In addition, ACT-R (of which ACT-R/Φ is an extension) has been used to develop cognitive models for tutoring systems [31]. We explore the architecture to implement a computational model, which can provide us with the details of the psychomotor skill learning process under a physiological constraint. Our approach allows more fine-grained and potentially accurate predictions of human performance and a better understanding of the learner and domain model that can improve the tutoring operations.

Over time we see the model use the production compilation mechanism (proceduralization) to combine several rules and speed up processing. Some rules (e.g., backswing) cannot be compiled because they need to represent the physical amount of time it takes to complete that physical action. Though proceduralization does combine some rules with declarative memory retrieval, some rules with declarative memory components remain even after 5,000 simulated practice swings (red, solid-line boxes). This tells us two things: (a) the model has not yet fully proceduralized the putting behavior process, and (b) the model will remain vulnerable to both procedural and declarative memory noise after many simulated runs. The latter is important as it affects the model's ability to follow the correct steps in as fast time as possible and theoretically leaves the possibility for incorrect facts be used to accomplish any task that has an explicit declarative memory component. If the model were to get to a point of using only compiled rules that do not require declarative memory retrieval, the risk of incorrect steps and information is reduced as the only incorrect behavior then would stem from an incorrect rule firing. These incorrect steps may arise from noise interference with the declarative memory retrieval process.

Computational understanding of the mechanisms will help us design instructions and feedback in ITSs. The physio-cognitive model can help explain the functional mechanisms related to behavioral adaptation during different breathing exercises. This model also moves us towards explaining how breathing exercises may affect movement through long-term learning stages (e.g., [34]). Fig. 2 shows the primary mechanisms of interaction between physiological and cognitive parameters (but see [35, 36] for a more in-depth discussion of the mechanisms).

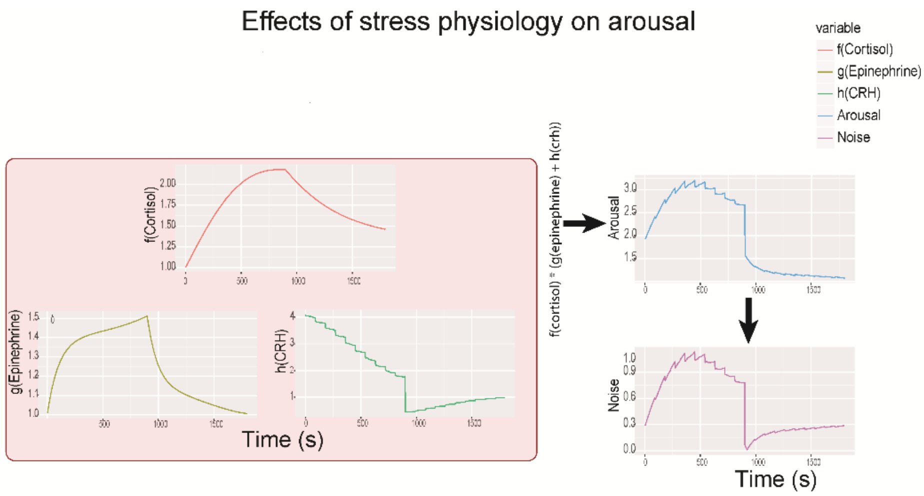

Fig 2. In ACT-R/Φ, Epinephrine (adrenaline), corticotrophin releasing hormone (CRH), and cortisol are physiological variables that combine to modulate arousal, which then modulates declarative memory noise.

In the model, the noise in declarative and procedural memory (in ACT-R the :ans and :egs parameters, respectively) is modulated by an arousal variable via a piecewise function that causes a U-Shaped effect. When arousal is *too high* or *too low*, noise is added to the subsymbolic memory equations (in ACT-R) that govern a cognitive model's ability to select the correct memory elements to complete a task. Arousal is affected by changes in several physiological variables, including epinephrine, corticotrophin releasing hormone (CRH), and cortisol. This effect on noise causes several systematic effects on psychomotor learning, affecting the model's ability to use the *correct* memory given a context (via noise) and implicitly affects learning, as the learning mechanisms in ACT-R are directly affected by the declarative and procedural memory elements used during a task. Thus, learning stages and a model's ability to move through later stages is modulated by arousal. Slow-breathing modulates this affect by reducing the effects of stress through its modulation of the balance between the para-sympathetic and sympathetic systems, and reduction of HPA-axis activation (see [35] for a more in-depth background and discussion on the mechanisms that govern this shift in the physiological portion of ACT-R/Φ).

4 The Pilot Study

We developed a study environment to test our theory-based model and report our pilot testing with one participant—the IRB is in preparation based on our pilot testing. The study intends to investigate putting performance during slow breathing. In this pilot testing, the participant performed 5 putting trials under the regular breathing condition, and then performed 5 additional putting trials with slow breathing—i.e., the participant breathes in for 4 s, holds still for 4 s, breathes out for 4 s, and holds still for 4 s.

The Study Environment. We extended GIFT to incorporate sensor data from an accelerometer in a smartphone. The data is relayed through a network connection, while the BioHarness sensor measuring respiratory rates relays data through Bluetooth. We have authored a series of GIFT courses that teach the tactical breathing technique shown in Fig. 3. We tested the study environment and its apparatus and collected pilot performance data from one participant.

A sensor for physiological data collection. The BioHarness sensor was used to measure and collect physiological data--e.g., the respiration rate (breathing rate: breaths per min.). A strap sensor measures the differential size of the expansion and contraction of the thoracic cavity. The sampling frequency of measuring respiratory activity and heart rates are 18 Hz and 250 Hz, respectively.

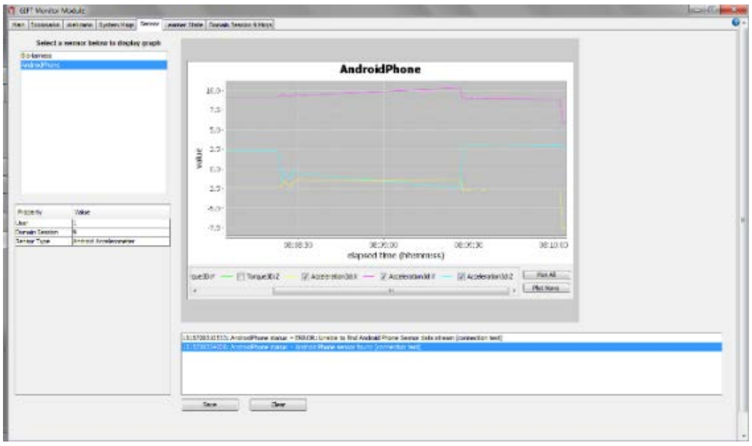

Fig 3. The GIFT study environment, showing data streaming from an external sensor after a domain session generation (an accelerometer in an Android phone).

A sensor for physical data collection. An accelerometer in a smartphone was used to identify motions during the physical task. Acceleration data has been used to categorize behavioral changes of an animal, such as resting, walking, jumping, standing, foraging [e.g., 27]. It is expected that physical motions in golf putting can be also identified and categorized. Fig. 3 shows an example acceleration data during the tactical breathing and putting. Golf swing and putting motions would consist of five critical points including the backswing point, the downswing point, the minimum peak point of x, y-axis, the maximum peak point of x, y-axis, and the end point [e.g., 26].

Testing the Apparatus and Study Environment. The purpose of data exploration is to identify the aforementioned body movements that are directly related to the putting task. The dataset shows the acceleration along with the three axes of the smartphone movement that is attached to the participant's left upper arm (x - sideways acceleration of the device; y - forward and backward acceleration of the device; and z - acceleration up and down). For the current pilot testing, we manually annotated the start and end of breath control and putting performance. Fig. 4 shows the acceleration plot of time frame 2:30 to 5:30 during the first set of 5 putting trials.

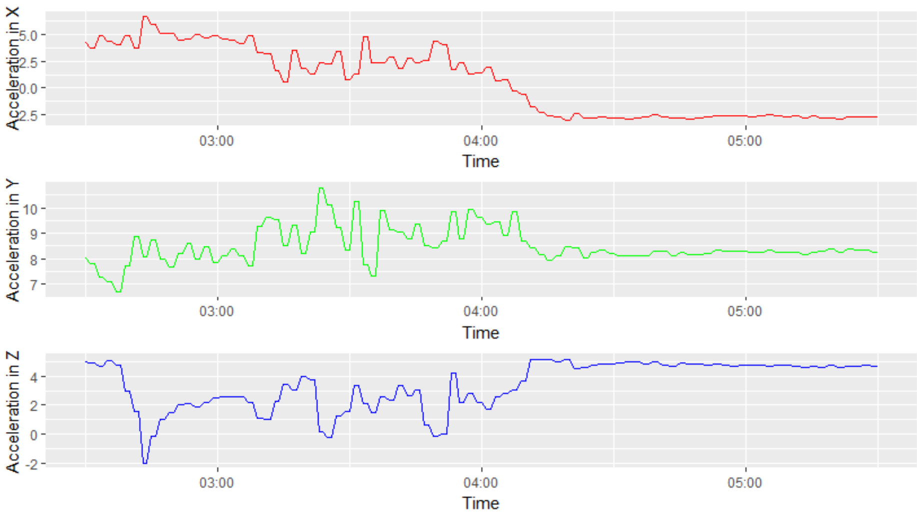

Fig. 4. Acceleration data in the time window ranging from 02:30 to 05:30.

Fig. 5 shows the breathing patterns from the two time frames (breaths per minute). The time frame (2:30 to 5:30) corresponds to the putting trials with regular breathing, and the time frame (5:30 to 8:30) corresponds to the putting trials with slow breathing. The median respiratory rate value with the first and third quantile values for the time frame (2:30 to 5:30, regular breathing) is 10.50 [9.00, 13.60], and for the time frame (5:30 to 8:30, slow breathing) is 8.70 [6.90, 11.00]. The participant's goal is to land the ball on the target by hitting the ball that is 183 cm away from the target. As a method to evaluate the performance of each putting trial, we measured the distance of the ball from the target after each trial. After measuring, the ball was removed from the green so that it does not interfere with the subsequent trial. During the regular breathing trials, the average distance from the target (post-shot) was 32.8 cm, and during the slow breathing, the average distance was 15.4 cm.

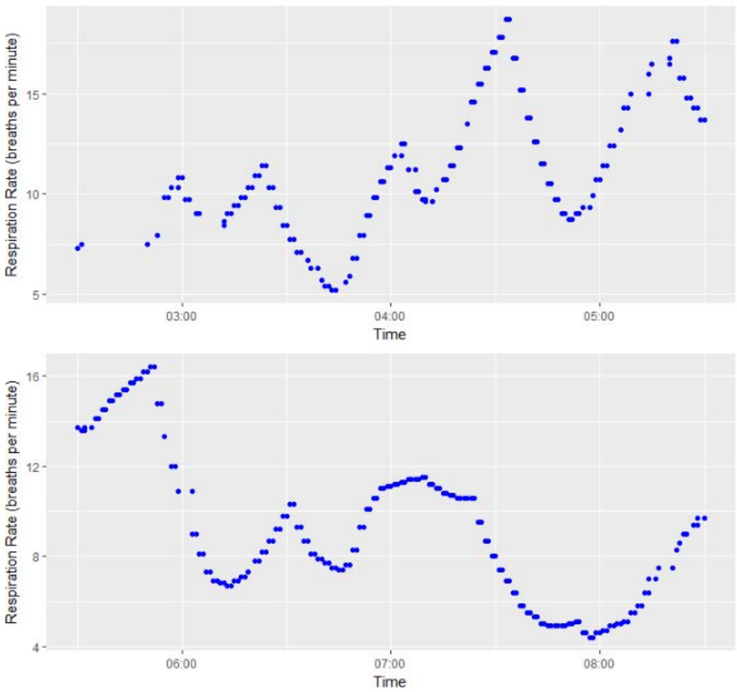

Fig 5. Respiratory activities in the two time frames (regular and slow breathing).

5 Conclusions and Discussion

We believe that the computational understanding of potential effects of slow breathing can make a useful contribution to the design of an instruction and feedback in a psychomotor tutor. The physio-cognitive model in ACT-R/Φ accounts for the several mechanisms of cognitive, physical, and physiological processes that affect human behavior. It can strengthen the domain and learner modeling capability because the physio-cognitive model is able to inform us of a theory-based instructional strategy in ITSs. That is, a representation of arousal in the physio-cognitive model modulates parameters that are important to learning and performance by influencing threshold and noise that are relevant to performance. At any given point of time, a physio-cognitive model may (or may not) be able to retrieve a declarative memory element, and to fire a production rule. Three stages of learning may be also affected, as arousal modulates declarative and procedural memory use during the learning process. Particularly, this modulation by arousal is represented in the declarative module through both activation values and harvesting of chunks, and in the procedural system through utility values, reinforcement learning, and production compilation in the ACT-R/Φ architecture.

Based on the different skill level, a physio-cognitive model can predict the process of learning, and it can be used to generate adaptive instructional strategies in terms of the learning stage.

Our pilot testing starts to explain the participant's performance and learning behavior by using the sensor data of physical motions and physiological states. Based on the study environment, it is necessary to further collect experimental data and to test the ACT-R/Φ theory by comparing data with the physio-cognitive model prediction, and to investigate the relationship between slow breathing and performance since the best score was observed under the slow breathing condition—the distance from the target was 3.6 cm.

We found that it is also worth utilizing a machine learning technique to assign the identified putting motions (backswing, downswing, ball contact, hitting, follow-thorough) to the acceleration data set. A machine learning technique has been used to process complex and large accelerometer data to classify and cluster animal behaviors [e.g., 27]. For the current pilot testing, we manually annotated the start and end of breath control with each putting trial. It will be necessary to consider how to deal with the large set of motion related acceleration data from multiple individuals and from multiple/hierarchical subtasks.

Though there is much work to be done with the physio-cognitive model, its integration to be used in GIFT, and the study, we believe the presented work is a positive step in developing an adaptive tutor that can determine cognitive state based on a combination of behavioral and physiological data. As we continue to develop adaptive systems for the learner, it will be useful to integrate the context of physiology to determine the learner state. This is especially important because we want to reduce maladaptive behavior in the warfighter as training continues to include more information to positively influence their mind-body state and performance.

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References

1. Lesgold, A.M., et al., *SHERLOCK: A coached practice environment for an electronics troubleshooting job*, in *Computer assisted instruction and intelligent tutoring systems: Establishing communication and collaboration*, J. Larkin, R. Chabay, and C. Scheftic, Editors. 1992, Lawrence Erbaum: Hillsdale, NJ.
2. Anderson, J.R., C.F. Boyle, and B.J. Reiser, *Intelligent tutoring systems.* Science, 1985. **228**(4658): p. 456-462.
3. Anderson, J.R., et al., *Cognitive modeling and intelligent tutoring.* Artificial Intelligence, 1990. **42**: p. 7-49.

4. Vanlehn, K., et al., *The Andes physics tutoring system: Lessons learned.* International Journal of Artificial Intelligence in Education, 2005. **15**(3): p. 147-204.
5. Nye, B.D., A.C. Graesser, and X. Hu, *AutoTutor and family: A review of 17 years of natural language tutoring.* International Journal of Artificial Intelligence in Education, 2014. **24**(4): p. 427-469.
6. Sottilare, R.A. and J. LaViola, *A process for adaptive instruction of tasks in the psychomotor domain*, in *Design recommendations for intelligent tutoring*, R. Sottilare, et al., Editors. 2016, US Army Research Laboratory: Orlando, FL. p. 185-194.
7. Sottilare, R.A. and J. LaViola. *Extending intelligent tutoring beyond the desktop to the psychomotor domain*. in *Interservice/Industry Training, Simulation, and Education Conference (I/ITSEC) 2015*. 2015. Orlando, FL.
8. Anderson, J.R., *How can the human mind occur in the physical universe?* Oxford Series on Cognitive Models and Architectures, ed. F. Ritter. 2007, New York, NY: Oxford University Press.
9. Rosenbloom, P. and A. Newell, *Learning by chunking: A production system model of practice*, in *Production system models of learning and development*, D. Klahr, P. Langley, and R. Neches, Editors. 1987, MIT Press: Cambridge, MA. p. 221-286.
10. Kim, J.W., et al., *Assessment of individual learner performance in psychomotor domains*, in *Design recommendations for intelligent tutoring systems: Assessment methods*, R. Sottilare, et al., Editors. 2017, U. S. Army Research Laboratory. p. 319-329.
11. Kim, J.W. and F.E. Ritter, *Learning, forgetting, and relearning for keystroke- and mouse-driven tasks: Relearning is important.* Human-Computer Interaction, 2015. **30**(1): p. 1-33.
12. Dancy, C.L., *ACT-RΦ: A cognitive architecture with physiology and affect.* Biologically Inspired Cognitive Architectures, 2013. **6**: p. 40-45.
13. Dancy, C.L., et al., *Using a cognitive architecture with a physiological substrate to represent effects of a psychological stressor on cognition.* Computational and Mathematical Organization Theory, 2015. **21**(1): p. 90-114.
14. Kim, J.W., et al., *A cognitive modeling approach - Does tactical breathing in a psychomotor task influence skill development during adaptive instruction?*, in *Augmented Cognition. Enhancing Cognition and Behavior in Complex Human Environments*, D.D. Schmorrow and C.M. Fidopiastis, Editors. 2017, Springer. p. 162-174.
15. Beilock, S.L., et al., *Haste does not always make waste: Expertise, direction of attention, and speed versus accuracy in performing sensorimotor skills.* Psychonomic Bulletin & Review, 2004. **11**(2): p. 373-379.
16. Beilock, S.L. and S. Gonso, *Putting in the mind versus putting on the green: Expertise, performance time, and the linking of imagery and action.* Quarterly Journal of Experimental Psychology, 2008. **61**(6): p. 920-932.
17. Grossman, D. and L.W. Christensen, *On combat: The psychology and physiology of deadly conflict in war and in peace*. 3rd ed. 2008, Belleville, IL: Warrior Science Publications.

18. Page, J.W., et al., *Brief mental skills training improves memory and performance in high stress police cadet training.* Journal of Police and Criminal Psychology, 2016. **31**: p. 122-126.
19. Bouchard, S., et al., *Using biofeedback while immersed in a stressful videogame increases the effectiveness of stress management skills in soldiers.* PLoS ONE, 2012. **7**(4): p. e36169.
20. Goldberg, B., et al., *Modeling expert behavior in support of an adaptive psychomotor training environment: A marksmanship use case.* International Journal of Artificial Intelligence in Education, 2017: p. 1-31.
21. Du, H., G.M. Youngblood, and P. Pirolli. *Efficacy of a smartphone system to support groups in behavior change programs*. in *Proceedings of the Wireless Health 2014 on National Institutes of Health*. 2014. Betheda, MD: ACM.
22. Pirolli, P., *A computational cognitive model of self-efficacy and daily adherence in mHealth.* Translational Behavioral Medicine, 2016. **6**(4): p. 496-508.
23. Nguyen, L.T., et al. *Superad: Supervised activity discovery*. in *Adjunct Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers*. 2015. Osaka, Japan: ACM.
24. Rai, A., et al. *Mining complex activities in the wild via a single smartphone accelerometer*. in *Proceedings of the Sixth International Workshop on Knowledge Discovery from Sensor Data*. 2012. ACM.
25. Wu, P., J. Zhu, and J.Y. Zhang, *Mobisens: A versatile mobile sensing platform for real-world applications.* Mobile Networks and Applications, 2013. **18**(1): p. 60-80.
26. Jung, C., *Measuring movement of golfers with an accelerometer*. 2012, KTH, School of Information and Communication Technology: Stockholm, Sweden.
27. Fehlmann, G., et al., *Identification of behaviours from accelerometer data in a wild social primate.* Animal Biotelemetry, 2017. **5**(1): p. 6.
28. Goldin, I., P.I. Pavlik Jr., and S. Ritter, *Discovering domain models in learning curve data*, in *Design recommendations for intelligent tutoring - Domain modeling*, R. Sottilare, et al., Editors. 2016, US Army Research Laboratory: Orlando, FL. p. 115-126.
29. Martin, B., *Constraint-based modelling: Representing student knowledge.* New Zealand Journal of Computing, 1999. **7**(2): p. 30-38.
30. Ohlsson, S., *Constraint-based modeling: from cognitive theory to computer tutoring–and back again.* International Journal of Artificial Intelligence in Education, 2016. **26**(1): p. 457-473.
31. Anderson, J.R., et al., *Cognitive tutors: Lessons learned.* Journal of the Learning Sciences, 1995. **4**(2): p. 167-207.
32. Koedinger, K.R., A.T. Corbett, and C. Perfetti, *The Knowledge-Learning-Instruction framework: Bridging the science-practice chasm to enhance robust student learning.* Cognitive Science, 2012. **36**(5): p. 757-798.
33. Paik, J., et al., *Predicting user performance and learning in human-computer interaction with the Herbal compiler.* ACM Transactions on Computer-Human Interaction, 2015. **22**(5): p. 1-26.

34. Kim, J.W., F.E. Ritter, and R.J. Koubek, *An integrated theory for improved skill acquisition and retention in the three stages of learning.* Theoretical Issues in Ergonomics Science, 2013. **14**(1): p. 22-37.
35. Dancy, C.L. and J.W. Kim. *Towards a physio-cognitive model of slow-breathing*. in *Proceedings of the 40th Annual Conference of Cognitive Science Society*. accepted. Wisconsin, USA: Cognitive Science Society.
36. Dancy, C.L., F.E. Ritter, and G. Gunzelmann. *Two ways to model the effects of sleep fatigue on cognition*. in *Proceedings of the 13th International Conference on Cognitive Modeling*. 2015. Groningen, Netherlands.